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3 **Predicting foraging wading bird populations in Everglades National Park**
4 **from seasonal hydrologic statistics under different management scenarios**
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Abstract

The ability to map relationships between ecological outcomes and hydrologic conditions in Everglades National Park (ENP) is a key building block for the restoration program, a primary goal of which is to improve conditions for wading birds. This paper reports on a model linking wading bird foraging numbers to hydrologic conditions in ENP. We demonstrate that seasonal hydrologic statistics derived from a single water level recorder are well-correlated with water depths throughout most areas of ENP, and are effective as predictors of wading bird numbers when using a nonlinear hierarchical Bayesian model to estimate the conditional distribution of bird populations given the seasonal statistics at the index location. Model parameters are estimated using a Markov Chain Monte Carlo procedure. Parameter and model uncertainty are assessed as a byproduct of the estimation process. Water depths at the beginning of the nesting season, the dry season recession rate, and the numbers of reversals in the recession are identified as significant predictors, consistent with the hydrologic conditions considered important in the production and concentration of prey organisms in this system. Long-term hydrologic records at the index location allow for a retrospective analysis (1952-2006) of foraging bird numbers showing low frequency oscillations in response to decadal fluctuations in hydroclimatic conditions. Simulations of water levels at the index location used in the Bayesian model under alternative water management scenarios produce variable numbers of foraging birds and the results provide criteria for linking management schemes to seasonal rainfall forecasts.

1. Introduction

Many of the adverse impacts on ecosystem function in the Everglades National Park (ENP; **Figure 1**) are caused directly or indirectly by altered regional hydrology [*Bancroft et al.*, 2002; *Craighead*, 1971; *Davis*, 1943; *Gleason*, 1984; *Loveless*, 1959; *Powell et al.*, 1989]. However, it is difficult to identify cause-and-effect relations between altered hydrologic patterns and ecosystem function in ENP because of the many factors involved, and because a long-term data record on each of the putative factors is needed to assess the relationships. Consequently, modeling studies [*Cline et al.*, 2006; *Gaines*, 2000; *Wetzel*, 2001] have been undertaken to create synthetic records that could represent the hydro-ecology of the region. Since the relationships in such models are largely prescribed or empirically estimated from relatively short records, it is difficult to rely solely on these models as tools for understanding or predicting the ecological outcomes in ENP consequent to hydroclimatic variations. A few authors [*Bancroft et al.*, 2002; *Russell et al.*, 2002] have tried to directly use data on a few species and hydrologic or climatic indicators to infer such relationships that could be used for subsequent management of ENP. This paper contributes to this literature.

A goal of ENP restoration project is to ensure that the ecological health of ENP improves as a direct result of management activities. Achieving hydrologic targets through the proper timing and amount of releases from control structures is a first step in the management process. Significant climate and weather variations in the region influence the ability to make releases and also determine the ecological outcomes. A predictive model for ecological outcomes given anticipated climate conditions and proposed releases is a basic building block for an adaptive management process. The development of such a model with a capacity for uncertainty analysis is the goal of the larger research project to which this paper contributes.

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84 Seasonal water depths in ENP depend on managed surface water releases from control

85 structures and on direct rainfall. On an annual basis and for ENP as a whole, direct rainfall is the

86 dominant component of the two water sources. However, the importance of the discharges

87 through the control structures increases during the dry season. These discharges are concentrated

88 along the northern boundary of ENP and they have their largest influence in the region directly

89 downstream called Shark Slough. The ecological responses to these discharges must be

90 quantified in order to effectively manage the Park and to guide the restoration effort. However,

91 given the large influence of rainfall on the system, the ecological responses to the managed

92 discharges must be placed within the context of larger-scale climatic factors. Here we link the

93 variations in the foraging populations of two wading bird species – a fundamental aspect of

94 Everglades' ecology – to hydrologic conditions in the National Park that result from rainfall and

95 managed releases.

96 Foraging patterns of wading birds have been a key issue in the Comprehensive Everglades

97 Restoration Plan (CERP), and monitoring of wading bird nesting success is a coordinated effort

98 between many agencies in Florida. Although other factors (e.g. prey conditions, migrations from

99 remote areas) may influence the foraging patterns of wading birds in ENP [*Cristol and Switzer*,

100 1999; *Gawlik*, 2002; *Houtman and Dill*, 1998; *Krebs and Cowie*, 1976; *Lima and Dill*, 1990;

101 *Safina and Burger*, 1985], it is likely that hydrologic conditions are a major driver that dominate

102 the underlying population dynamics in the Park [*Cezilly et al.*, 1995; *Frederick and Collopy*,

103 1989; *Gawlik*, 2002; *Powell*, 1987; *Russell et al.*, 2002; *Smith*, 1995; *Spalding et al.*, 1993;

104 *Strong et al.*, 1997]. Previous studies [*Russell et al.*, 2002] have shown an inverse relationship

105 between the number and degree of dry season disruptions (short term reversals in the recession

106 of surface water) and wading bird foraging patterns.

107   Our study seeks to quantify the response of wading bird foraging numbers to selected

108   seasonal statistics of the daily water level The long term goal is to improve wading bird

109   outcomes in ENP through the use of climate forecasts and adaptive water release policies from

110   control structures such that a better water level trajectory results for the upcoming season from

111   the perspective of wading bird foraging success. This entails climate and water level forecasts in

112   ENP for each candidate release policy and the connection of the resulting water level forecasts to

113   potential wading bird populations. This paper presents one critical piece of this exercise – the

114   ability to predict seasonal wading bird foraging numbers from water level statistics at a single,

115   centrally-located gauge (P33) located below the control structures. We show that water levels

116   through much of ENP, especially those in regions important for wading bird foraging, are highly

117   correlated with water levels at P33. The relatively long record (>50 yrs) at this gauge also

118   provides a basis for linking wading bird foraging patterns in ENP to decadal-scale climate

119   variability.

120   This paper develops a Hierarchical Bayesian Model that relates the population of two

121   dominant wading birds, the Great Egret (*Casmerodius albus*) and White Ibis (*Eudocimus albus*),

122   to key seasonal statistics of the water levels at P33. Water levels at P33 and potential wading bird

123   foraging populations are then predicted, again using a Bayesian scheme, based on rainfall and

124   inflow volumes under different management scenarios for the Park. We take a Bayesian

125   approach so that model and parameter uncertainty can be quantified. Probabilistic, seasonal

126   climate forecasts will eventually be used for decision analysis regarding managed releases, and

127   since these decisions must also incorporate uncertainty information to ensure a specified

128   reliability in outcomes, a Bayesian approach for the entire process is attractive to properly assess

129   the propagation of this uncertainty in modeling and analysis.

2. Study Area and Data

The greater Everglades ecosystem extends from the southern edge of Lake Okeechobee to Florida Bay. The southern terminus of the system has been preserved as ENP, one of the most widely recognized wetlands in the world. The historic ecosystem was once characterized by large expanses of shallow, slowly moving surface water (called sheetflow) with seasonally fluctuating water levels controlled primarily by rainfall and runoff from Lake Okeechobee. Hydropatterns over much of this region have been altered through various forms of land use change and management practices related to regional water supply and flood control. The once contiguous wetlands have been compartmentalized by a series of canals and levees that, along with a network of pumps, weirs, and gated culverts, are the primary means by which water levels are controlled and deliveries made to the population centers and natural areas. As a result of these modifications, sheetflow patterns in the system have been altered, causing deviations from historic water level fluctuations and an overall decline of ecosystem function within ENP. Most notably, wading bird populations are estimated to have declined by 90% relative to their historic levels [Ogden, 1994]. ENP has a sub-tropical climate with a distinct wet season in the summer and a dry season in the winter. Almost, 75% of the annual precipitation falls during May-October with monthly precipitation amounts ranging between 0.0 and 20.0 inch. Overland sheetflow from northern contributing zones into ENP is a fraction of the historical amounts. Ecologic restoration of ENP brings to the fore the challenge of how to deliver the right amount of water to the Park at the right times to the right locations.

The primary data considered are historical rainfall records, water stages and the foraging abundance of *Great Egret and White Ibis*. Water level data are taken from the P33 gauge which is shown below to be directly related to overall hydrologic conditions in the Park, and for which

153   long-term reliable data are readily available from 1952 to 2007. Seasonal variation in water stage

154   at P33 is illustrated in **Figure 2(a)**.

155   Wading bird foraging data from the Systematic Reconnaissance Survey Flights (SRF)

156   [*Norton-Griffiths*, 1978; *Russell et al.*, 2002] were used. The SRF involve flying at a fixed

157   altitude and speed across a study area on a predetermined transect while observers count animals

158   in a strip of land on either side of the aircraft. The SRF surveys were initiated to give South

159   Florida's operational resource managers a tool to assess wildlife populations. Past work to

160   explore the effects of hydrology on SRF-derived wading bird distribution and abundance data is

161   documented in *Russell et al.*, [2002], *Bancroft et al.*, [1992, 2002], and *Porter and Smith* [1984].

162   The SRF wading bird survey was initiated in 1985. The data are updated every month from

163   December through May, the dry season in south Florida, and once in August. [*Russell et al.*,

164   2001] provide details of the SRF wading bird surveys. In the present work the wading bird data

165   were derived by aggregation from any grid cell in which each species was ever recorded by SRF

166   from 1985 to 2006. Seasonal variations in *Great Egret* and *White Ibis* populations are shown in

167   **Figure 2(b-c)**.

168

169   3.0 Preliminary Analyses

170   3.1 Relationship between P33 stage and water depths in ENP

171
172   During the dry season, large numbers of wading birds forage within ENP and tend to

173   concentrate along Shark Slough. Aerial survey records (1985-present) show the numbers of

174   wading birds foraging in the Slough and throughout ENP fluctuate on an annual basis. These

175   fluctuations have been linked to water depths at the beginning of the dry season and the

176   subsequent recession rates by [*Russell et al.*, 2002]. However, the hydrologic data used by

177   [*Russell et al.*, 2002] were derived from qualitative aerial observations and not based on actual

178   gauge data. This is because water level recorders have been scattered non-uniformly in the Park

179   and operational for different time periods. Synoptic water depths for the entire Park were

180   therefore not available for the period of record matching the bird surveys. Recent installations of

181   automated gauge stations have increased the spatial coverage of water level measurements and

182   allowed for interpolation between these stations. Updated, grid-based (400 m^2) topography data

183   [*Desmond*, 2003] facilitates the conversion of the interpolated water levels to water depths for

184   most of ENP.

185   Water level fluctuations across ENP are highly correlated. A linear correlation map between

186   daily water stages from January to April 2006 at P33 and daily water depths derived from

187   interpolation of gauge data throughout ENP is illustrated through the colored contour maps in

188   **Figure 3**. A high correlation is observed between stages at P33 and water depths throughout

189   ENP over this period. The correlations are highest along the longitudinal axis of Shark Slough

190   and in areas of similar elevations during both the dry season and wet season. Control structures

191   discharge water across the northern boundary of ENP directly into the Slough and have less

192   effect on water levels in adjacent areas of higher elevation, or in areas close to the border canals.

193   Thus, there is some decrease in correlation between stages at P33 and water depths outside of the

194   Slough, such as in some of the marl prairie regions. For the period from 2000-2007 we found an

195   average r^2 correlation coefficient of 0.75 (ranging from 0.66 to 0.95) between January-April

196   daily water depths at P33 and water levels at seven principal gauges (NE2, NP201, EVER6, CP,

197   P36, NP46, CR2) in ENP, each representing one of the landscape classifications shown in Figure

198   3. With this information we consider water levels at P33 a useful indicator of water depths

199 throughout most of ENP, particularly in areas of Shark Slough where wading bird foraging is

200 concentrated.

201   Observations of foraging *Great Egret* and *White Ibis* in May of each year (1985-2006) and

202 are also displayed in Figure 3. High wading bird counts can be noted in those regions of ENP

203 that show the highest correlation with P33 water levels. As a consequence, water levels at P33

204 may be useful to infer the suitability of hydrologic conditions for wading birds throughout the

205 Park.

206 **3.2 Identifying Suitable Predictor Variables from the P33 data**

207

208   Bird foraging patterns are affected by many different factors such as prey availability

209 [*Gawlik*, 2002; *Krebs and Cowie*, 1976; *Lima and Dill*, 1990; *Safina and Burger*, 1985] and the

210 threat of predation [*Cristol and Switzer*, 1999; *Houtman and Dill*, 1998; *Lima and Dill*, 1990].

211 Hydrologic conditions are also known to play a role [*Powell* 1987). Changes in the historical

212 pattern of water level fluctuation are considered to be a significant factor that determines

213 foraging patterns and the abundance of bird populations in ENP [*Cezilly et al.*, 1995; *Frederick*

214 *and Collopy*, 1989; *Gawlik*, 2002; *Powell*, 1987; *Smith*, 1995; *Spalding et al.*, 1993; *Russell et*

215 *al.*, 2002; *Strong et al.*, 1997].

216   It is important to recognize that hydrologic conditions may be related to other factors

217 influencing wading bird foraging [*Gawlik*, 2002]. For example, the density and distribution of

218 vegetation in ENP is an example of a habitat factor related to hydrologic conditions that may

219 affect foraging patterns. Marsh vegetation types and density in the Everglades are known to

220 change with alterations to hydroperiod [*Ross et al.,* 2003; *Armentano et al.,* 2006; *Saunders et al.,*

221 2006], and these changes in vegetation distribution/density may affect the habitat quality for

222 foraging wading birds. The populations of wading birds in areas outside ENP, (e.g. the Water

223 Conservation Areas) and the migrations of birds to and from these areas may also be a

224 determinant of the foraging patterns observed during the SRF flights. The impact of these

225 migrations on the SRF observations is not well known and was not included in our model. Since

226 little information on the impacts of factors such as vegetation types or migration on foraging

227 patterns is available, we focus on hydrologic statistics of within-season variation in P33 stage as

228 potential predictors of foraging numbers for the two species of interest.

229   Everglades wading birds nest in the December – May dry season, and successful foraging

230 during this period can be considered a prerequisite for successful nesting [*Russell et al.,* 2002;

231 *Frederick and Ogden,* 2003]. Foraging success in the dry season is dependent on water depths

232 being low enough to allow standing, and on appropriate surface water recession rates which

233 concentrate prey in the low-lying areas [*Kushlan*, 1986*; Frederick and Collopy*, 1989*; Gawlik,*

234 2002]. Disruptions to the dry season recession caused by winter rainfall events or from managed

235 water releases tend to reduce foraging success because of the resulting prey dispersal [*Frederick*

236 *and Ogden*, 2003]. Too rapid recession rates or too low water levels in December may shorten

237 the nesting season, although it is important to consider that the impacts of these and other

238 hydrologic factors on foraging/nesting are often species-dependent [*Frederick and Spalding*,

239 1994]. For this initial analysis, the number of *Great Egret* and *White Ibis* in May at the end of the

240 dry season are selected as the predictands reflecting aggregate hydrologic variables calculated

241 from January - April. These two species were chosen because their white color makes them easy

242 to identify in the SRF flights, and these data are therefore less subject to error. As in *Russell et al.*

243 (2002) bird counts in May were chosen because late-dry season foraging numbers can be

244 considered an indicator of nesting initiated earlier in the season. Similar models could be

245 developed using data collected during any dry season month and for other species of wading

246 birds. Models which incorporate within-season variability in foraging and nesting patterns with

247 changes in the regional and local-scale hydropatterns will improve understanding of the specific

248 relationships between hydrology, foraging, and the success of individual colonies [*Bancroft et al.,*

249 *1994*]. The objective of this paper represents a step in this direction by demonstrating the

250 development of a robust analytical framework capable of linking ecological outcomes to

251 hydrologic indicators in a manner that is useful to managers and restoration planners.

252   Now we consider the seasonal statistics of the daily water levels recorded at P33 that may be

253 useful predictors of the May bird count. The approach followed is generally similar to that used

254 by [*Russell et al.*, 2002], except that the predictors are derived from actual daily water level data

255 from a single location, P33, instead of using the gridded qualitative aerial observations of water

256 level at a monthly scale.

257   The procedure used to develop seasonal water stage statistics as predictors from the daily

258 water stage data at P33 is illustrated in **Figure 4**. First, consider a linear decline of stage with

259 time during the middle of the dry season (January through April) representing the seasonal

260 recession of the water table.   For this recession, a linear regression of stage versus time into the

261 season provides the intercept as an estimate of the mean of initial water level, and the slope as an

262 estimate of the recession rate. Once this recession behavior is estimated, a disruption can be

263 defined as a positive residual from the linear regression line. For each season, we can then

264 compute the number of disruptions, a standard deviation of disruption, a maximum consecutive

265 disruption, the average water stage, the intercept and the recession slope at P33 as potential

266 predictors.

267   A stepwise regression procedure together with exploratory data analysis was used next to

268 screen these potential predictors for each bird count. Finally, the initial water level, the averaged

269　water level and the number of disruptions from January through April were selected as predictors.

270　A smooth surface fit using a Cross validated Thin-plate smoothing spline [*Wahba*, 1990] of the

271　birds as a function of initial water stage and disruption is shown in **Figure 5**. Note that the bird

272　counts are positively correlated with initial stage and average stage, and are negatively correlated

273　with the number of disruptions as can be expected. As may also be expected, the initial and

274　average stage for the season are correlated. The correlations across the three predictors and the

275　two predictands, and partial correlations for each prediction are provided in **Table 1**. Based on

276　these partial correlations it is apparent that while the predictors are correlated with each other,

277　they still contribute useful additional predictive information. An examination of Figure 5

278　illustrates that the relationship of bird count with water level is nonlinear. Bird counts initially

279　increase with average or initial water level, but decrease or level out for high stage.

280　Consequently, a quadratic relationship between the predictand and these predictors may be

281　appropriate [*Russell et al*., 2002].

282　　A K-means [*Spath*, 1985] cluster analysis was applied to the standardized time series of the

283　three predictors and population counts for each bird species. The intention was to see how these

284　attributes group together. Box plots of the number of birds and the predictors for the three

285　clusters identified are shown in **Figure 6**. The first cluster corresponds to medium water stage

286　and relatively low disruption. The median bird populations are the highest for this cluster. The

287　White Ibis population has high variation for this cluster, but is still generally higher than for the

288　other clusters. Cluster 2 has the highest water levels and a medium level of disruption. It maps to

289　a middle category of median bird population, but with high variation in the Great Egret bird

290　count. The third cluster corresponds to the lowest water levels and the highest disruption

291 frequency and maps on to the lowest bird counts for both species. The nonlinearity of the

292 relationship between the predictors and the predictand is further illustrated by this analysis.

293

4.0 A Predictive Model for Foraging Birds Populations

295

296   A hierarchical Bayesian model is developed for the seasonal prediction of seasonal

297 populations of *Great Egret* and *White Ibis* using the selected hydrologic variables, specifically

298 the initial water stage, the average water stage and the number of disruptions. The model

299 considers that the population of each bird species follows a log normal distribution with time

300 varying mean $\mu(t)$ and a constant variance σ. A quadratic model for the mean $\mu_j(t)$ for bird

301 species *j* in terms of each predictor is then formulated as follows:

302

303   (1) $Z_j(t) \sim LN(\mu_j(t), \sigma_j)$

304   (2)

305    $\mu_j(t) = \beta_{1j} + \beta_{2j} \cdot IWS(t) + \beta_{3j} \cdot IWS(t)^2 + \beta_{4j} \cdot AWS(t) + \beta_{5j} \cdot AWS(t)^2 + \beta_{6j} \cdot DIS(t) + \beta_{7j} \cdot DIS(t)^2$

306   Where $Z_j(t)$ represents the bird count for species *j* for season *t*, with mean $\mu_j(t)$ and

307 standard deviation σ_j (the variance is taken to be a constant over time after some initial

308 experimentation); *IWS* is initial water stage, *AWS* is averaged water stage and *DIS* is number of

309 disruptions at P33 from January to April.

310   Each of the parameters in the model above is considered as a random variable with a given

311 probability distribution. A schematic of the model is presented in **Figure 7**. We note that the

312 correlation of the observed abundance between the two bird species is 0.85, and hence it may be

313 useful to consider pooling these data in a regression conditioned on the same predictors. The

314 hierarchical Bayesian model used here provides an objective way to choose the degree of pooling.

315 First we apply the regression to foraging bird population data standardized by dividing the raw

316 series by the mean annual bird population for the corresponding series. Next, we assume that the

317 regression coefficients for each bird species for each predictor come from a common distribution

318 with a common mean and variance. If this variance is small then effectively we have a pooled

319 regression. Conversely, if this variance is large, then independent regressions for the two species

320 result. If the number of bird species introduced into the model increases, then this procedure

321 would still apply and would lead to a better estimate of the mean and variance of the common

322 regression coefficient.

323   The hierarchical regression models are solved in a Bayesian framework. Non-informative

324 priors are assumed for each of the parameters and hyperparameters (e.g., β_{ij}, $\mu_{\beta_{ij}}$, $\mu_{\mu_{\beta_i}}$, σ_j) and

325 their optimal values are selected through a maximization of the posterior likelihood of observing

326 the data. A Markov Chain Monte Carlo (MCMC) procedure is used. In particular, the Gibbs

327 sampling approach to MCMC [*Gilks et al.*, 1995] has been used in this study. We chose to run

328 three chains simultaneously searching for optimal parameters. The evolution of each chain was

329 monitored to check for convergence to a common value. Selection of the hyper-priors and the

330 appropriateness of the prior distributions and the model structure were judged by the deviance

331 information criterion (DIC) [*Berg et al.*, 2004]. All computations were performed in Matlab

332 using Winbugs (*Spiegelhalter et al.*, 2003). To assess convergence for each parameter the

333 [*Gelman and Rubin*, 1992] 'shrink factor' was computed. This factor compares the variation in

334 the sampled parameter values within and between chains, and it describes how much the increase

335 in the number of iterations improves the estimates. [*Gelman and Rubin*, 1992] suggest running

336 Gibbs sampler chains until the estimated shrink factors are less than about 1.2 for all parameters.

337 Winbugs produces scale reduction factors that are very close to 1 for the fixed effects. Values

338 around 1 were obtained after 10,000 iterations.

339   **Table 2** summarizes key results for each regression coefficient. The posterior mean,

340 standard deviation, and 95% credible interval are derived using MCMC as noted above (the

341 detailed estimates of Hyperparameters are summarized in Appendix). Recall that the initial and

342 average water stages are correlated predictors. Hence, it is not possible to uniquely identify one

343 or the other as a predictor, and given the results in Table 1, both the linear and the quadratic

344 terms in these two variables are retained. For both species, the quadratic term in number of

345 disruptions has a posterior 95% interval that brackets zero. This observation is consistent with

346 the observation from the relationship in Figure 5, where the relationship appears linear. So, one

347 could consider the deletion of this term from the model. The fit of the various models was

348 compared using the DIC as calculated in Winbugs [*Spiegelhalter et al.*, 2003]. The lower the

349 DIC value, the better the model fits the data. The model that includes the quadratic term has a

350 lower DIC score than the model that does not include it, so we retained this term as well. Unlike

351 the case for classical linear regression, where predictors are selected and putative causes are

352 argued for based on a hypothesis test for the significance of particular regression coefficients, in

353 the Bayesian formulation, the intention is to present posterior conditional distributions for the

354 $Z(t)$ that reflect both the uncertainty in estimating the parameters, and the model uncertainty,

355 i.e., the variation in $Z(t)$ not explained by the model. By including an additional term in the

356 model and considering the uncertainty in it, we may be understating the standard deviation σ

357 ascribed to variations around the conditional mean, i.e., the residual or noise term. However, if

358 the interest is in a posterior interval for $Z(t)$, rather than in the attribution of variance to the noise

359 term or to a predictor, then the inclusion of an additional predictor does not change the results.

360   The time series of observed wading birds and the values predicted at ENP in May, using

361   Bayesian quadratic regression with the three predictors for 1985–2006 are shown in **Figure 8**.

362   The posterior mean and the 5% to 95% posterior uncertainty bounds are provided. The posterior

363   mean corresponding to a cross validation procedure is also shown. The cross-validation process

364   as implemented here removes seven years from the training set, estimates the regression

365   coefficients with the remaining data, and then predicts the birds for the year that was omitted.

366   Model predictive ability is quantitatively assessed to judge the degree to which the model

367   simulation matches the actual observations. One can utilize different statistics of efficiency to

368   measure the goodness of fit or prediction skill. [*Legates and McCabe*, 1999] have critically

369   reviewed many of the principal statistics of efficiency. *Nash and Sutcliffe*, [1970] defined the

370   Coefficient of Efficiency (CoE) which ranges from minus infinity (poor model) to 1.0 (perfect

371   model). The CoE has been widely used to evaluate the performance of prediction models (e.g.,

372   [*Wilcox et al.*, 1990]). For more details regarding goodness of fit measures, see [*Legates and*

373   *McCabe*, 1999] and [*Willmott et al.*, 1985]. The statistics used in our study are summarized in

374   **Table 3** and the performance of the model according to these measures is shown in **Table 4**. The

375   *Great Egret* and *White Ibis* posterior means predicted by the model have a correlation of

376   approximately 0.8 with the observed series with a CoE 0.7. The model was also applied to the

377   data from 2000 to 2006, which were originally withheld from the fitting process. No significant

378   change in results is noted. Analysis of residuals (observed –posterior mean) for the model for

379   *Great Egret* and *White Ibis* supported the assumption of zero mean, independently and

380   identically normally distributed errors. Jarque-Bera test for goodness-of-fit to a normal

381   distribution [*Judge et al.*, 1988] and the Shapiro-Wilk parametric hypothesis test of composite

382 normality [*Royston*, 1995] were performed, and the hypothesis that error has a normal

383 distribution is not rejected at the 5% and 10% level.

384   The model developed above is now applied for retrospective prediction of wading bird

385 foraging numbers for the period 1952-1984 for which daily P33 stage data is available but bird

386 data is not. The results are illustrated in **Figure 9**. The long-term trends for P33 average water

387 stage, disruption and rainfall are indicated by Lowess [*Cleveland*, 1979] smooth lines

388 superimposed on graphs of time series in **Figure 10**. The concurrent decadal to multi-decadal

389 variability in the relevant time series is shown. An interesting feature is the increase in foraging

390 bird population post-1995, even though the seasonally averaged rainfall and P33 stage do not

391 show any marked trends. We note, however, that the disruption time series reveals a decreasing

392 trend over the same time period, reinforcing the earlier assessment that both the stage and the

393 disruption frequency are important indicators for foraging conditions. The trends in foraging

394 numbers in the period before systematic observations are available are consistent with our

395 expectations from the nonlinear model. The period from 1962 to 1970 is marked by relatively

396 low water levels and higher disruption frequency, and translates into lower bird counts. On the

397 other hand the higher bird counts around 1960 and 1980 again correspond to average to higher

398 water levels with a lower disruption frequency. These results rely on the assumption that the

399 relationship between P33 and water levels in the other areas of ENP where wading birds are

400 known to forage remained relatively constant over the complete period of record. Some changes

401 in water management regulation schedules and policies have occurred during this time period.

402 However, the central location of P33 in Shark Slough gives confidence that it has consistently

403 reflected the general hydrologic condition of the areas where wading birds tend to forage. Our

404 goal in presenting these results is to set the stage for a comparative evaluation of different release

405 policies from the control structures that translate into different AWS, IWS, and DIS values at

406 P33 and therefore, different numbers of foraging bird populations.

5. Modeling water levels at P33

407

408

409   A Bayesian approach is developed to relate observed water levels at P33 to a combination of

410 hydrologic predictors representing the water budget parameters at the site. The model considers

411 that over time period t the water level at P33, $Z(t)$, is normally distributed with a time-varying

412 mean $\mu(t)$ and a constant variance σ. A quadratic model of the mean $\mu(t)$ in terms of each

413 predictor is then formulated as follows:

414    $Z(t) \sim N(\mu(t),\sigma)$ (3)

415
$$\mu(t) = \beta_1 + \beta_2 \cdot P_{33}(t-1) + \beta_3 \cdot \delta_R(t) \cdot R(t-1) + \beta_4 \cdot \delta_R(t) \cdot R(t-1)^2$$
$$+ \beta_5 \cdot \delta_I(t) \cdot I(t-1) + \beta_6 \cdot \delta_I(t) \cdot I(t-1)^2$$
                                                                (4)

416    $\delta_R = \begin{cases} 0 & R \le 0 \\ 1 & R > 0 \end{cases}, \qquad \delta_I = \begin{cases} 0 & I \le 0 \\ 1 & I > 0 \end{cases}$ (5)

417 where, P_{33} is daily average water stage, R is total daily rainfall and I is the daily average rate of

418 surface water inflow through upstream control structures into ENP. A delta function is employed

419 to differentiate the zero and the non-zero case for R and I. The form of the equation in this case

420 reflects the univariate relationships between the hydrologic parameters known to occur at this

421 site, namely, that mean water levels increases asymptotically with I and R, and that P33(t) is

422 linearly correlated to P33(t-1). Non-informative priors were selected and a three chain Gibbs

423 sampling approach to MCMC [*Gilks et al.*, 1995] was employed to solve for the parameters in

424 Matlab using Winbugs [*Spiegelhalter et al.*, 2003]. A *Gelman and Rubin* [1992] 'shrink factor'

425 criteria of 1 in the MCMC was used to establish the parameter values (**Table 5**) and their

426 variation within and between chains. The model coefficient of variation, the coefficient of

427   efficiency, and the bias show very high fidelity with observed values during separate calibration

428   (1978-1987) and verification (1988-2006) periods.

429   **6.0 Impacts of alternative water management policies on water levels**
430   **and foraging populations**
431
432   The impacts of water release policies were investigated by linking predictions of

433   seasonal P33 water levels (and the corresponding AWS, IWS, and DIS) based on different inflow

434   scenarios to the Bayesian model of foraging bird populations. In this scheme P33 water levels

435   were first calculated using (3) & (4) with calibrated parameter values and with variable inflow

436   volumes corresponding to different management scenarios for the period 1986-2000. The

437   "Baseline" case represents P33 and foraging population predictions using measured rainfall and

438   inflows discharging into ENP. Five alterative inflow management scenarios were then tested and

439   are ordered here based on the total amount of water delivered to ENP. Rainfall amounts do not

440   vary among scenarios. The first scenario, "No inflow", assumes zero releases from the surface

441   water control structures located across the northern boundary of the Park. Surface water releases

442   for the "Minimum inflows" scenario are mandated by federal law (PL 91-282) with the objective

443   of avoiding catastrophic damage to the ecosystem during drought periods [*Light and Dineen*

444   1994]. The "Rainfall Plan" regulates inflows to ENP as a function of rainfall in the northern

445   contributing basins according to a formula derived by the SFWMD [*Neidrauer and Cooper*,

446   1989; *Light and Dineen*, 1994]. The Interim Operating Plan "IOP" represents the current

447   management scheme for ENP in place since 2000, while the Combined Structural and

448   Operational Plan "CSOP" scenario is a management scheme accompanying a large-scale

449   restoration project designed to increase and alter the timing of ENP inflows. Inflows into ENP

450   under the IOP and CSOP scenarios were derived from the South Florida Water Management

451   Model (SFWMM, http://www.evergladesplan.org/pm/recover/system_wide_modeling.aspx), a

452   regional-scale hydrology model for south Florida. For Jan-April of each year, the AWS, IWS,

453   and DIS were calculated and used to predict wading bird populations generated in each scenario

454   according to (2).

455   Aggregate statistics on foraging populations calculated over the full 1986-2000 period of

456   record were found to obscure the differences between scenarios because of the high interannual

457   variability in rainfall and predicted bird populations. We therefore divide the analysis into two

458   time periods representing below-average (1986-1990), and average to above-average (1991-

459   2000) rainfall conditions. During the low rainfall period normalized AWS and IWS are

460   consistently below average for all scenarios (**Table 6**). DIS values are above average for all

461   scenarios during this period, with the exception of the restoration scenario CSOP. The CSOP

462   scenario also produced relatively higher AWS, and together the low DIS this scenario resulted in

463   the highest average numbers of foraging birds during 1986-1990 compared to all other scenarios

464   (**Figure 11**). Student's *t* tests indicate the differences in 1986-1990 populations under these

465   scenarios were not significant due to the short record and high variance caused by the very low

466   rainfall in 1989-1990. However, the results are consistent across scenarios and show that

467   foraging populations during low rainfall periods are predicted to decrease with declining inflows

468   to ENP, with the fewest birds occurring under the "No inflows" and "Minimum Flows" scenarios.

469   The period 1991-2000 is characterized by average to above-average rainfall, increasing

470   AWS and IWS, and below-average DIS for all scenarios. These conditions resulted in higher

471   numbers of foraging birds compared to the low rainfall period across all scenarios. In general,

472   however, and in contrast to the low rainfall period, the scenarios which delivered relatively less

473   water to ENP (e.g. "No inflows", "Minimum inflows" and the "Rainfall plan") produced the

474 highest numbers of foraging birds. From this analysis, we conclude that during wet periods, high

475 rainfall alone is capable of maintaining AWS and IWS within optimal ranges for wading birds

476 without the addition of managed releases into ENP. DIS values for all scenarios were also lower

477 during high compared to low rainfall conditions and this improved wading bird outcomes.

478 However, the relative decrease in DIS was less apparent under the CSOP scenario. The benefits

479 of higher rainfall to wading bird foraging patterns were therefore reduced in this scenario

480 compared to the others. Anomalous water depths which exceeded the optimal conditions for

481 wading birds during the high rainfall period under both the CSOP and IOP scenarios also

482 reduced the number of birds predicted under these scenarios compared to the others. This is

483 particularly apparent during 1995, when rainfall was ~20% higher (175 cm) than average, and

484 the Great Egret foraging populations under the "No inflow" scenario were 3 and 4 times greater,

485 respectively, than those predicted under IOP or CSOP. Remarkably, the White Ibis populations

486 produced by the "No inflow" scenario were 10-14 times higher than IOP and CSOP during 1995.

487 White Ibis populations in general showed larger responses to management scenarios compared to

488 Great Egrets.

489   This scenario analysis points to the potential impacts of managed inflows on foraging

490 conditions in ENP. During low rainfall periods, managed releases are necessary to maintain

491 favorable water levels. However, during high rainfall periods these releases may contribute to

492 raising water levels above optimal values. Over the entire 1986-2000 period, the largest average

493 numbers of foraging birds of both species were predicted under the "Minimum inflow" and the

494 "Rainfall Plan" scenarios. However, this is largely because the majority of the period is

495 characterized by high rainfall conditions when the scenarios which restrict inflows performed

496 relatively well. We suggest it is therefore important to consider the performance of these

497   scenarios in a larger context determined by rainfall timing and amount. Optimizing foraging

498   conditions for wading bird species over longer time periods is likely to require adaptive release

499   schedules which incorporate real-time information on water levels, rainfall, and climatic drivers

500   [e.g. *Kwon et al.,* 2006]. Of the five analyzed here, the management scenario most closely tied to

501   climatic conditions is the "Rainfall Plan", and while it did not produce the highest numbers of

502   Great Egret or White Ibis during either the low or high rainfall periods, this scenario did produce

503   the highest median number of foraging birds when the species were combined over the full

504   period of record (3200 birds yr^{-1}). Similar climate-based approaches to managing inflows into

505   ENP could further improve habitat quality for foraging birds. It is recommended additional

506   analyses be conducted using population data from other species to investigate the broader

507   ecological outcomes of rainfall-driven management plans.

508 **7.0 Summary and Discussion**

509

510   Water depths and their fluctuation in the dry season have an impact on wading bird habitat

511   suitability in ENP. This is well known and many indices have been developed to assess habitat

512   suitability in terms of modeled or observed variables. The work presented here represents a

513   departure from the existing literature that has evolved on this topic. We chose to step back and

514   focus on the predictability of an observed measure of ecological outcomes – estimates of the bird

515   foraging populations – contingent on some identifiable measures of hydrologic conditions in the

516   region. Given the existing literature on the subject, the effort started with modest expectations,

517   and the best and longest available time series for bird populations and a hydrologic time series

518   were used to develop an analysis. A particular challenge in this context was to identify seasonal

519   statistics of daily hydrologic variation that could suitably inform an analysis of aggregate end of

520   season foraging bird populations in a regression framework. After a certain amount of

521   exploratory work that is presented in a rather condensed form in this paper, a set of predictors

522   that was causally plausible and statistically informative was selected. Initial, nonparametric

523   regression modeling suggested a nonlinear relationship between the response and the predictors.

524   This led to the development of a nonlinear regression model for each bird species in terms of the

525   same set of predictors. Recognition that the populations of the two species are highly correlated

526   with each other suggested that something could be gained by pooling the two regression

527   problems, in terms of characterizing and reducing the uncertainty in the model coefficients. This

528   problem was formulated as a Hierarchical Bayesian regression model and the parameters and

529   hyperparameters of the model were estimated using Markov Chain Monte Carlo methods with a

530   standard approach for checking for convergence and adequacy of model diagnostics. The results

531   of the investigation are presented through posterior conditional densities that include the

532   contribution of parameter uncertainty, and also through cross-validated prediction. The

533   performance statistics are quite impressive for this kind of a model, and provide hope that a

534   simple model such as presented here can be a useful, communicable building block in a strategy

535   that proposes changes in hydrologic conditions through management interventions in a way

536   designed to improve habitat suitability and hence bird outcomes.

537   Short records and a large number of potential hydroclimatic and other biophysical predictors

538   generally make it difficult to reliably assess the potential response to changed hydrology and the

539   uncertainty associated with models linking ecological outcomes to hydrologic conditions. This

540   challenge is prominent even though several inter-connected spatio-temporal models of hydrology

541   and ecology have been developed specifically for the Park. This situation has been partially

542   addressed in this paper. For instance, knowledge of the initial water level, together with

543   probabilistic climate forecasts, and a proposed water release policy, could be used to estimate

544 both the probability distributions of average water level in the upcoming season, and the

545 disruption frequency. These could then be jointly used to estimate the probability distribution of

546 birds present at the end of the season using the model developed here. Water release policy

547 refinements could then be pursued in an optimization framework to "deliver" desired population

548 levels with a specified reliability. These policies would include release guidelines that are

549 adaptive within the season, indexed to initial and current water levels, and recent rainfall. Models

550 that map observed and forecast daily rainfall, current stage, and water release from control

551 structures into future stage at P33 would need to be formulated and used as part of a release

552 policy to provide adaptive rules to guide releases such that intra-seasonal hydrologic conditions

553 evolve in a way that leads to improved end-of-season bird outcomes. Work on these aspects is

554 ongoing, and includes verification of the intermediate variables of interest, while connecting the

555 drivers as identified directly to the outcome. Future work will incorporate daily rainfall

556 simulations capturing common or unique aspects of low frequency variation using Wavelet

557 Autoregressive models [*e.g. Kwon et al.*, 2006; 2007].

558

Acknowledgements

566

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702

703 **Figure captions**

704

705 **Figure 1** Everglades National Park is located at the southern tip of the state of Florida, USA. The
706 hydrologic monitoring station P33 is identified by the star near the center of Shark Slough.

707

708 **Figure 2** Seasonal trends and variation (box plots) in monthly values of a) water stage at P33,
709 and foraging abundance of b) Great Egret and c) White Ibis from 1985 to 2006. Observations of
710 wading birds are not available in June, July, September, October and November.

711

712 **Figure 3** *Great Egret* (a) and *White Ibis* foraging abundance in May 2006, community types, and
713 correlation of water depths to P33 during the dry season. The colored contour map shows the
714 correlation between grid-based water depths in ENP and P33 water levels during the period from
715 January to April 2006. The black circles represent the number of birds in May 2006 and the size
716 of the circle is proportional to the number of birds. The right hand side of the coverage that is not
717 labeled is outside of ENP and subject to different water management practices, resulting in
718 depths with low correlations with P33 and few wading birds. The small area of low correlation
719 on the left hand side indicates a tidal influence not present in other parts of the coverage.

720

721 **Figure 4** Three predictors derived from water stage at the P33 station. One is the seasonal
722 average water stage (AWS), the second is the intercept of the best fit line for the decline in stage
723 over the dry season, a measure of the initial water stage (IWS) at the beginning of the foraging
724 season) and the final predictor is the number of disruptions (DIS) to the recession rate with the
725 progression of the dry season.

726

727 **Figure 5** Smooth surface fit using a Cross validated Thin-plate smoothing spline [*Wahba*, 1990]
728 of a) log (*Great Egret*) and b) log (*White Ibis*) as a function of initial water stage and disruption
729 illustrates the nonlinearity of the relationship. Note the generally linear relationship of bird
730 counts with the number of days with disruptions, and the more complex relationship with stage.

731

732 **Figure 6** Box plots of the number of birds and the predictors initial water stage (IWS), average
733 water stage (AWS), and disruption (DIS) given three clusters.

734

735 **Figure 7** Hierarchical Bayesian Regression Model, μ indicates the location parameter (mean)
736 and σ indicates scale parameter (variance).

737

738 **Figure 8** Bayesian model predictions (solid line) and observed bird counts at ENP in May (open
739 circle) using AWS, IWS, and DIS values at P33 as predictors for 1985–2006. Model output
740 refers to the posterior mean from the Bayesian model, and Cross-validated value refers to the

741 posterior mean estimated with the model without using these data (2000-2006). *r* values shown
742 at the top right refer to the correlation between the posterior mean and observed values. The
743 uncertainty bounds represent the 5% and the 95% of the posterior conditional distribution.
744
745 **Figure 9** Retrospective analysis of wading bird foraging numbers. Model predictions (solid line)
746 and observed birds at ENP in May (open circle), using Bayesian quadratic regression (Eqn. 2)
747 and AWS, IWS, and DIS derived from 1952-2006 water levels at P33. The late 1950s and early
748 1960s were marked by significant hydrologic manipulations in the regional water management
749 system.
750
751 **Figure 10** The long-term trends for P33 average water stage (top), disruption (middle) and
752 rainfall (bottom panel) are indicated by Lowess [*Cleveland*, 1979] smooth lines superimposed on
753 graphs of time series. The concurrent decadal to multi-decadal variability in the relevant time
754 series is shown.
755
756 **Figure 11** Alternative inflow management scenarios produce variable numbers of foraging Great
757 Egret and White Ibis in ENP from 1986 – 2000.
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765 **Table 1** Correlation coefficients for the three predictors initial water stage (IWS), average water
766 stage (AWS) and number of disruptions (DIS) and the two predictands (Great Egret and White
767 Ibis foraging populations), including partial correlations
768

	Great Egret	White Ibis
Bird, IWS/AWS,DIS	-0.131	0.035
Bird,AWS/IWS,DIS	0.173	-0.136
Bird,DIS/IWS,AWS	0.834	0.861
Bird,IWS/AWS	0.831	0.865
Bird,IWS/DIS	0.117	-0.208
Bird, AWS/IWS	0.831	0.865
Bird,AWS/DIS	0.025	-0.163
Bird, DIS/IWS	0.117	-0.208
Bird,DIS/AWS	0.025	-0.163

769 † *IWS is initial water stage, AWS is averaged water stage and DIS is number of disruptions at P33 from January to April.*
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778 **Table 2** Model parameters and associated uncertainty bounds for wading bird foraging
779 populations
780

	Node	Description	Mean	Stand. Dev.	2.50%	Median	97.50%
Great Egret Population Model	β_1	*Intercept*	0.201	0.133	-0.070	0.202	0.461
	β_2	*Initial W.S*	-0.018	0.206	-0.415	-0.021	0.374
	β_3	*Initial W.S ^{2}*	-0.252	0.077	-0.401	-0.253	-0.099
	β_4	*Averaged W.S*	0.382	0.190	0.000	0.388	0.759
	β_5	*Averaged W.S ^{2}*	-0.098	0.123	-0.347	-0.099	0.132
	β_6	*No. of Disruption*	-0.289	0.087	-0.465	-0.287	-0.122
	β_7	*No. of Disruption ^{2}*	-0.102	0.068	-0.238	-0.101	0.029
White Ibis Population Model	β_1	*Intercept*	0.146	0.164	-0.194	0.151	0.458
	β_2	*Initial W.S*	-0.519	0.265	-1.077	-0.510	-0.021
	β_3	*Initial W.S ^{2}*	-0.261	0.087	-0.437	-0.261	-0.094
	β_4	*Averaged W.S*	0.649	0.241	0.170	0.643	1.117
	β_5	*Averaged W.S ^{2}*	-0.231	0.138	-0.504	-0.231	0.052
	β_6	*No. of Disruption*	-0.471	0.111	-0.687	-0.470	-0.260
	β_7	*No. of Disruption ^{2}*	-0.094	0.082	-0.252	-0.096	0.073

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786 **Table 3** Regression model performance measures

Statistics	Formula
Correlation Coefficient	$r = \dfrac{\sum_{t=1}^{N}(O_t - \overline{O})(P_t - \overline{P}_t)}{\left(\sum_{t=1}^{N}(O_t - \overline{O})^2\right)^{0.5}\left(\sum_{t=1}^{N}(P_t - \overline{P})^2\right)^{0.5}}$
Coefficient of Efficiency	$CoE = 1 - \dfrac{\sum_{t=1}^{N}\left(O_t - P_t\right)^2}{\sum_{t=1}^{N}\left(O_t - \overline{O}\right)^2}$
Normalized Bias	$Bias = N^{-1}\sum_{t=1}^{N}(O_t - P_t)/O_t$

[1]N is the sample size and P is the model-simulated data and O is the observed data.

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790 **Table 4**. Model performance for wading bird foraging predictions.
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Predictors	R	CoE	Normalized Bias
Great Egret	0.84	0.72	-2%
White Ibis	0.84	0.71	-6%

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Table 5 Model performance measures, parameters and associated uncertainty bounds for daily predictions of P33 water levels based on hydrologic parameters.

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P33	*Measure*	*Cal. 30%*	*Ver. 70%*	*Node*	*Description*	*Mean*	*Stand. Dev.*	*2.50%*	*Median*	*97.5%*
Daily				β_1	*Intercept*	6.151	0.906	4.823	5.908	7.761
water	*r*	0.981	0.989	β_2	*$P33_{t-1}$*	0.913	0.012	0.892	0.916	0.931
level				β_3	*$Rainfall_{t-1}$*	0.440	0.078	0.289	0.440	0.596
prediction	CoE	0.963	0.978	β_4	*$Rainfall_{t-1}^2$*	-0.017	0.013	-0.043	-0.017	-0.008
				β_5	*$Inflow_{t-1}$*	0.398	0.083	0.245	0.396	0.561
	Bias (m)	−0.001	−0.057	β_6	*$Inflow_{t-1}^2$*	-0.007	0.033	-0.069	-0.007	0.058

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Table 6 Mean and (standard deviation) of predicted hydrologic variables and Great Egret and White Ibis foraging populations for current, baseline conditions and five alternative ENP water management scenarios

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	1986-1990*				
Scenario	**AWS**	**IWS**	**DIS**	**Great Egret**	**White Ibis**
Baseline	-0.93 (0.51)	-1.16 (0.60)	0.52 (0.56)	761 (415)	701 (443)
No inflows	-1.20 (0.39)	-1.40 (0.48)	0.59 (0.38)	517 (199)	441 (200)
Minimum inflows	-0.94 (0.46)	-1.09 (0.51)	0.73 (0.38)	689 (283)	617 (289)
Rainfall plan	-0.95 (0.51)	-1.19 (0.58)	0.31 (0.68)	768 (445)	748 (599)
IOP	-0.85 (0.61)	-1.17 (0.61)	0.31 (0.59)	801 (381)	714 (414)
CSOP	-0.83 (0.62)	-1.19 (0.58)	-0.14 (0.90)	928 (503)	909 (589)

	1991-2000**				
Scenario	**AWS**	**IWS**	**DIS**	**Great Egret**	**White Ibis**
Baseline	0.36 (0.94)	0.20 (1.07)	0.07 (1.10)	1346 (532)	1130 (630)
No inflows	-0.56 (0.45)	-0.56 (0.65)	-0.95 (0.79)	1486 (581)	1898 (914)
Minimum inflows	-0.26 (0.46)	-0.22 (0.66)	-0.76 (0.66)	1774 (570)	2092 (844)
Rainfall plan	0.05 (0.76)	-0.09 (0.87)	-0.72 (0.68)	1698 (607)	1716 (779)
IOP	0.51 (0.99)	0.23 (1.05)	-0.68 (0.80)	1578 (663)	1359 (728)
CSOP	0.51 (0.95)	0.20 (1.11)	-0.49 (0.88)	1488 (563)	1199 (548)

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807 * Period of below average rainfall
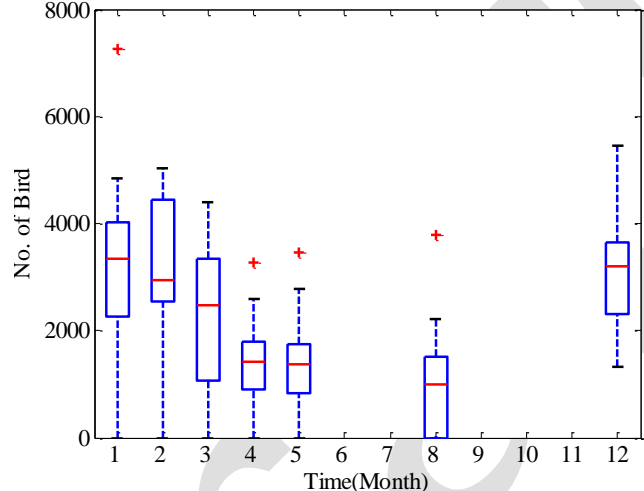808 ** Period of average to above average rainfall

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812   **Figure 1**

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818 **Figure 2**

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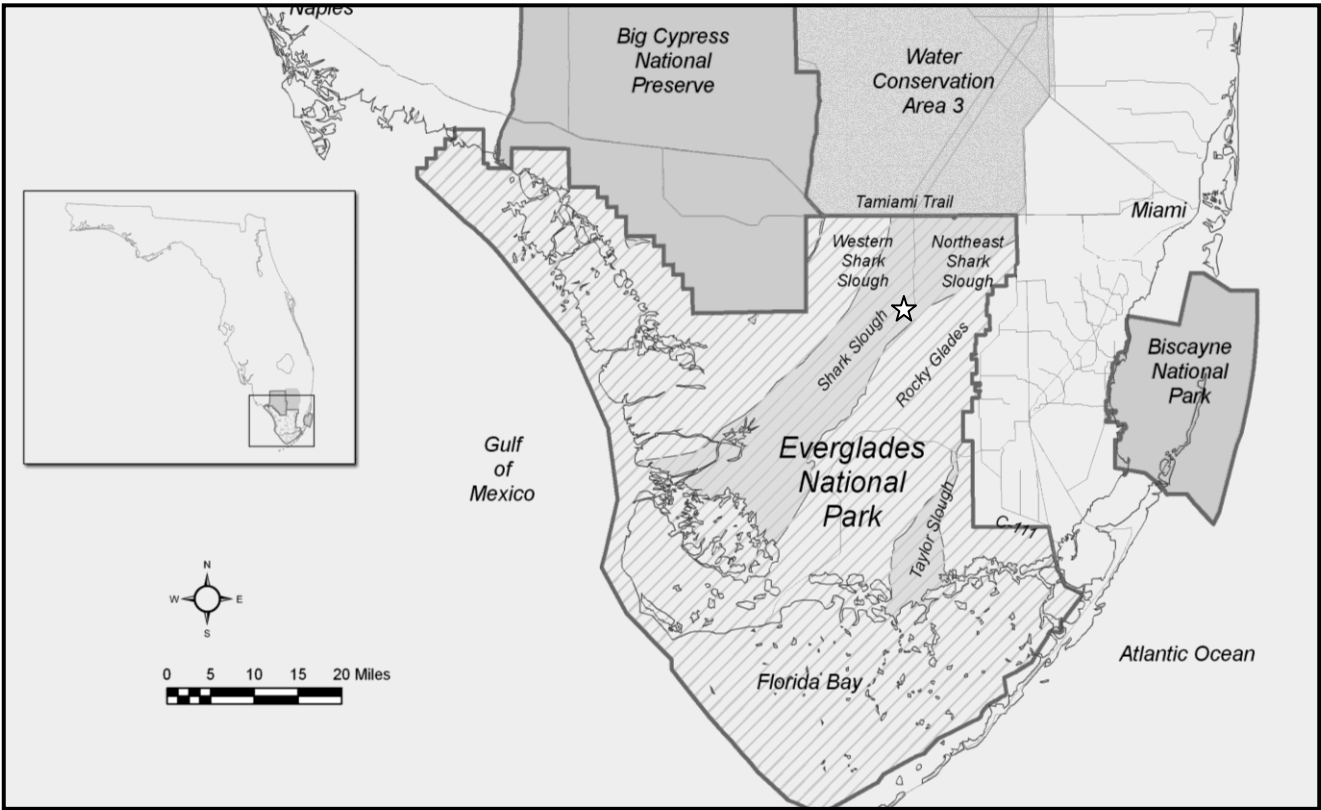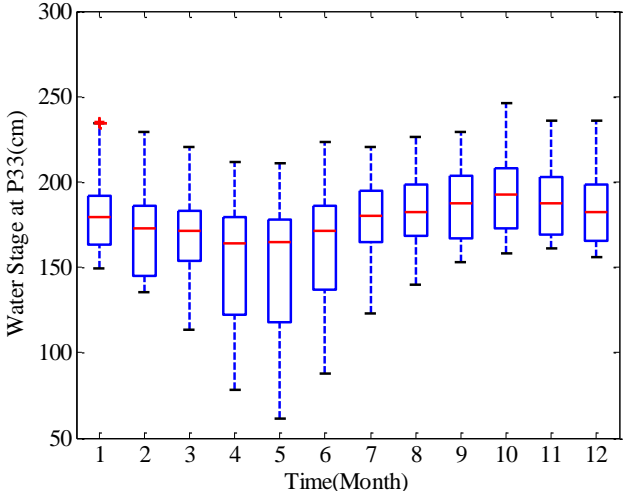
821 *a) Water Stage at P33*   *b) Great Egret*   *c) White Ibis*

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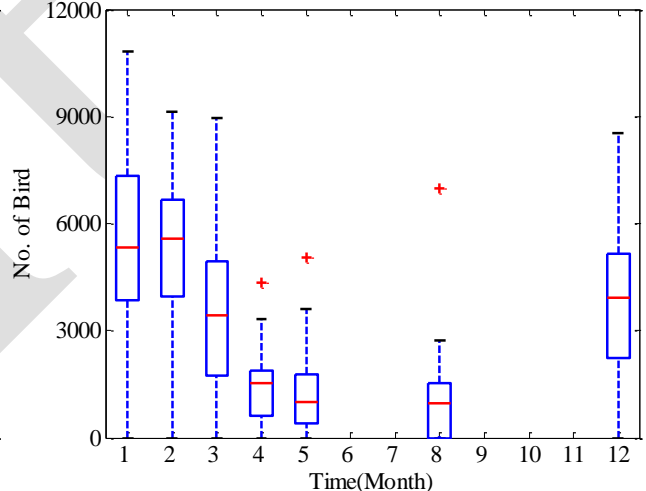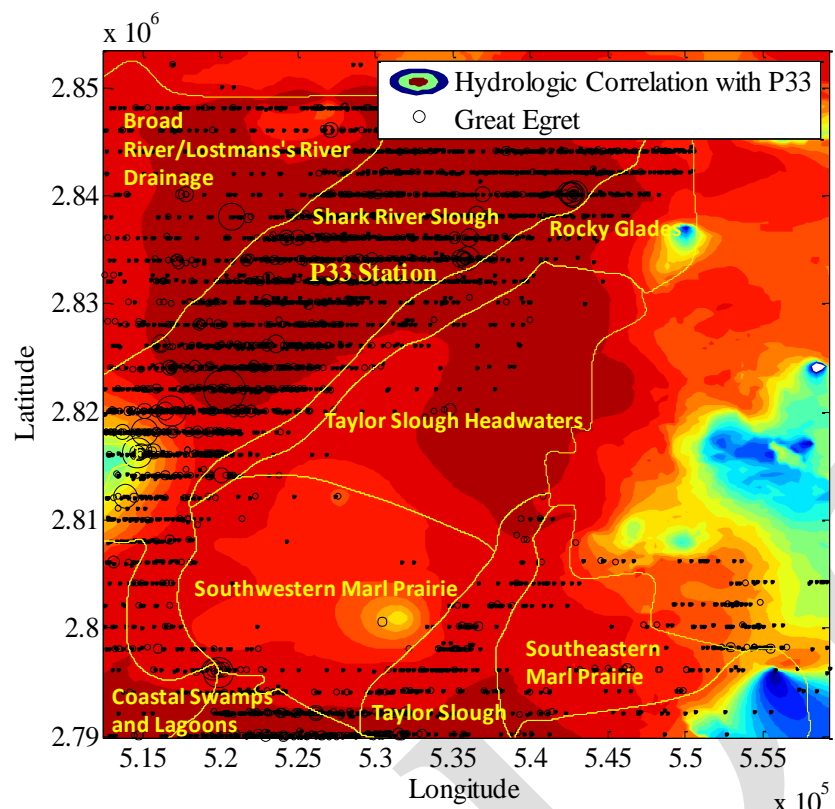**Figure 3**

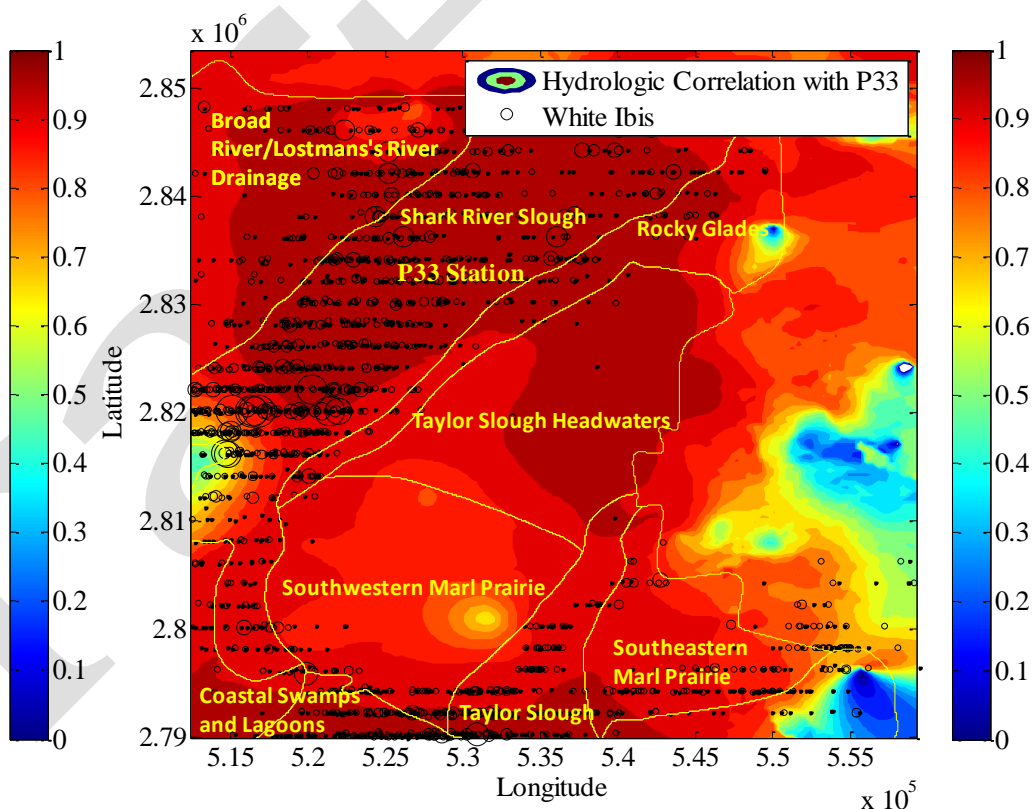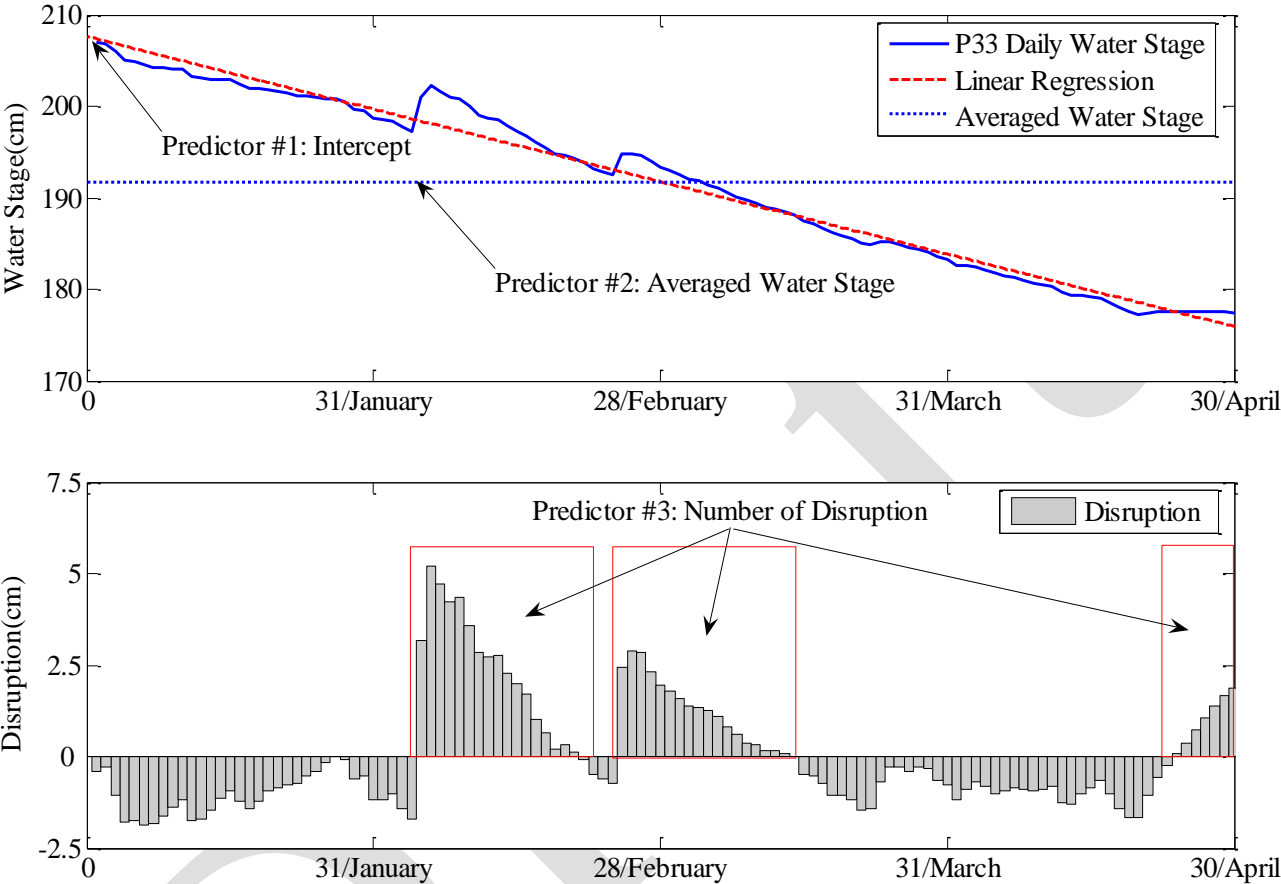*a) Great Egret*   *b) White Ibis*
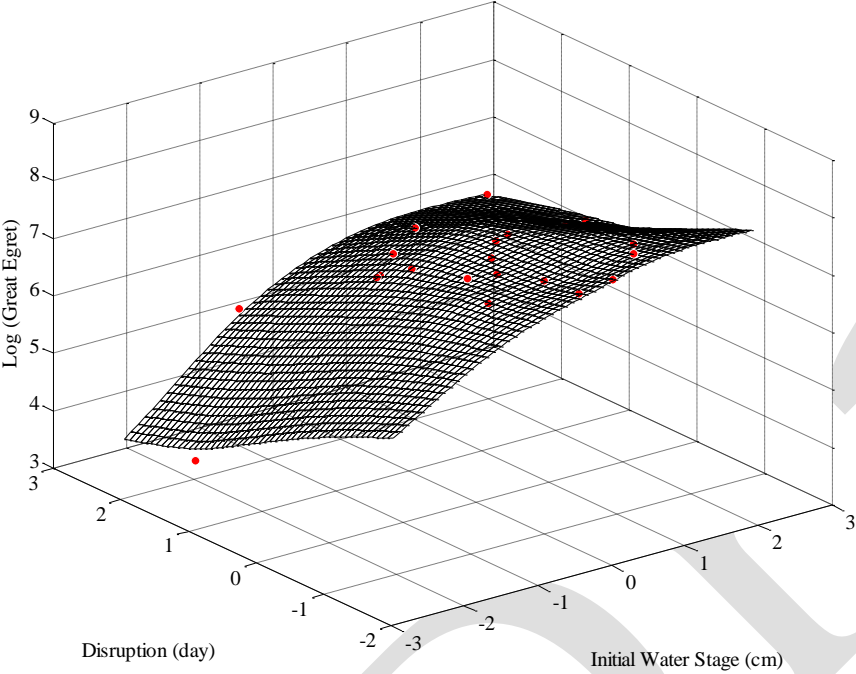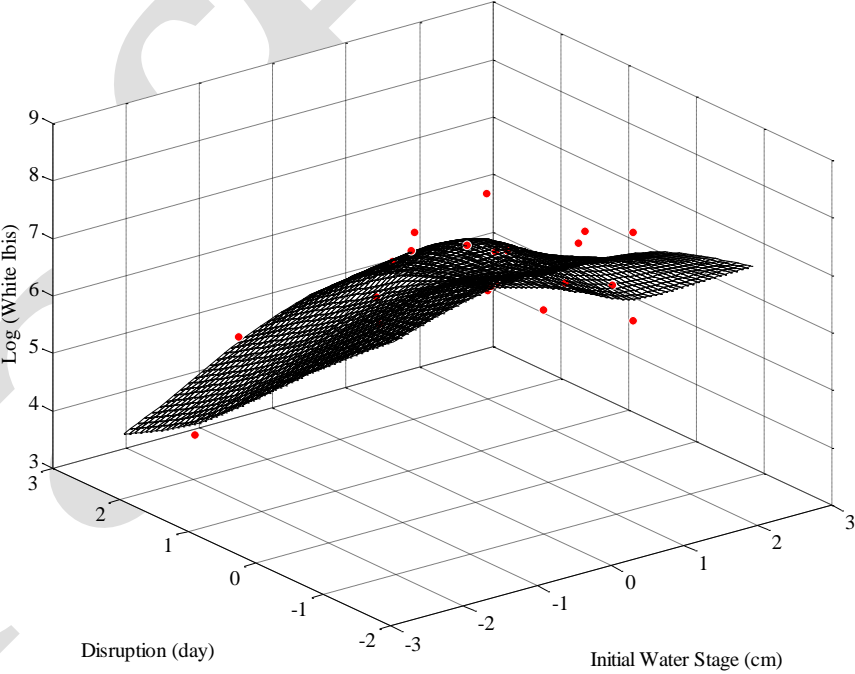
Figure 4

836 **Figure 5**

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836 **Figure 5**

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843   **Figure 6**

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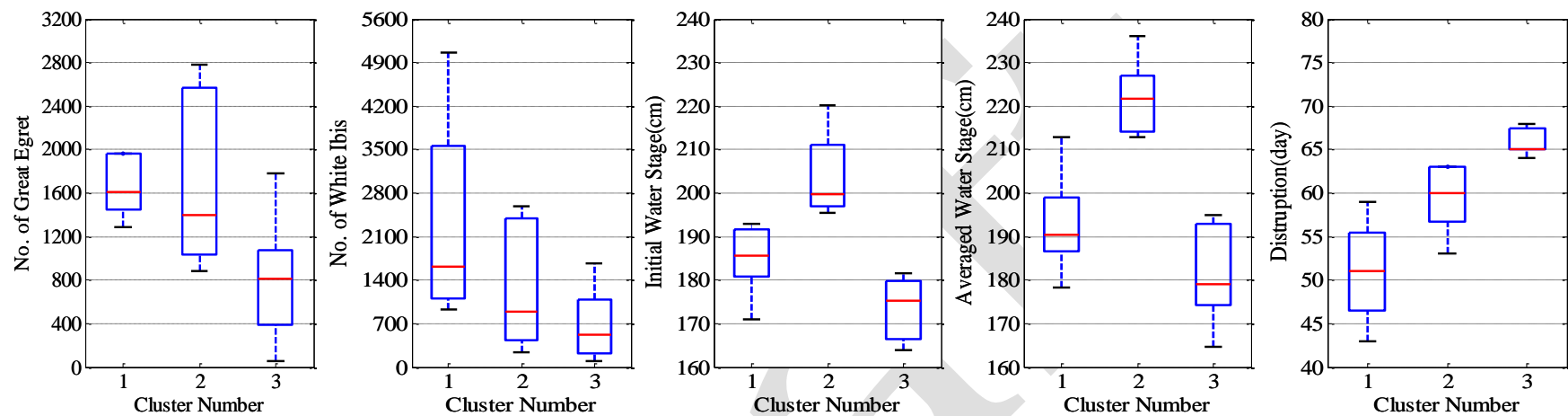
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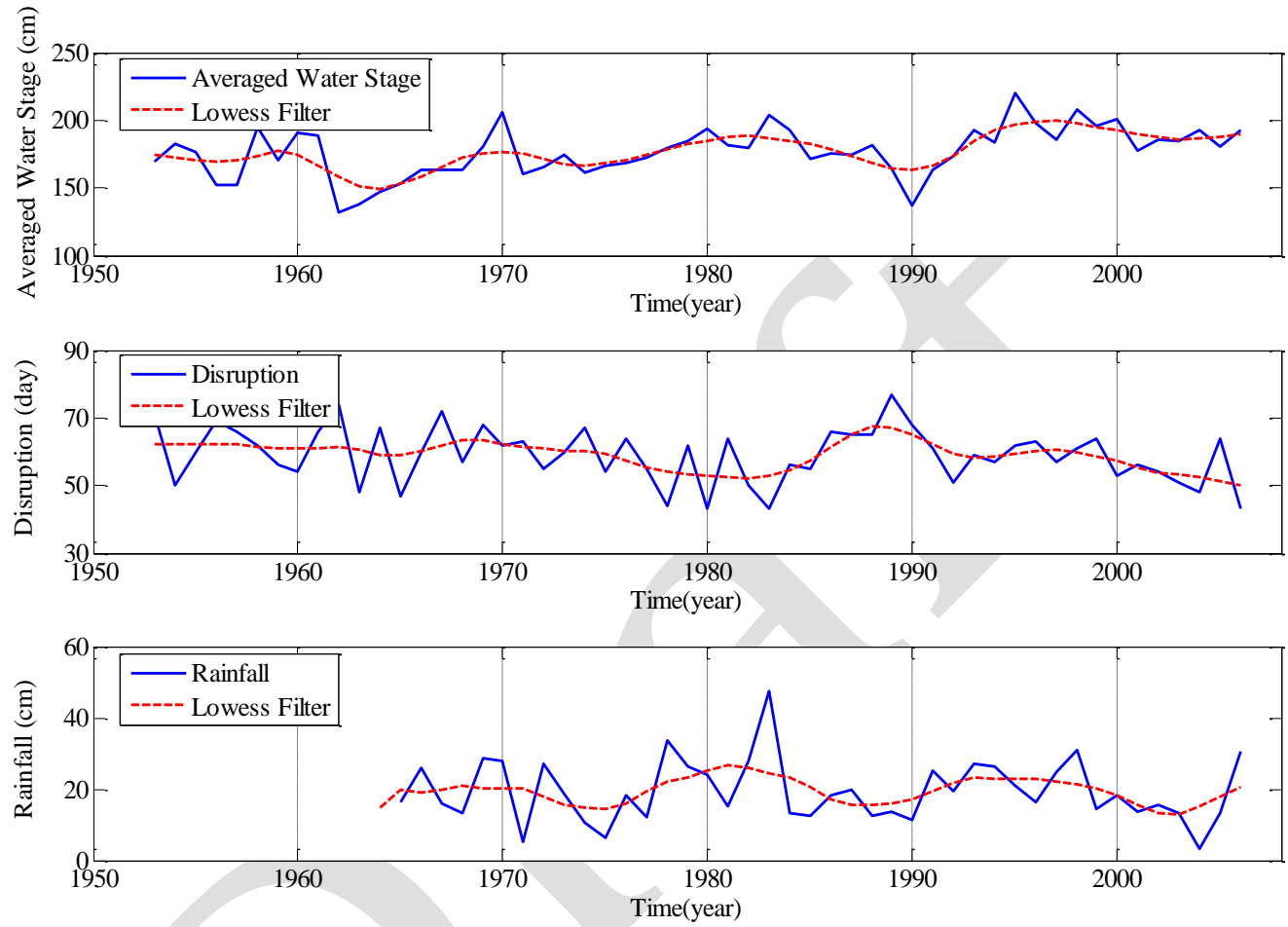846

847 **Figure 7**

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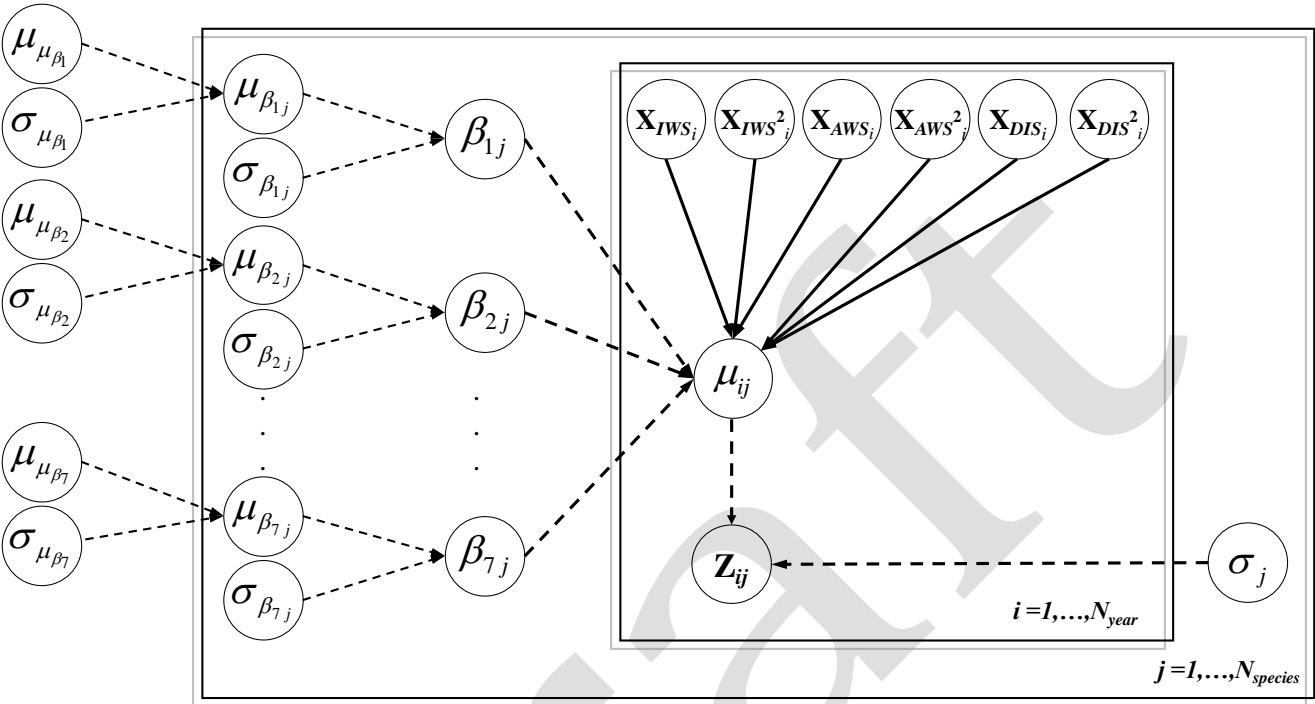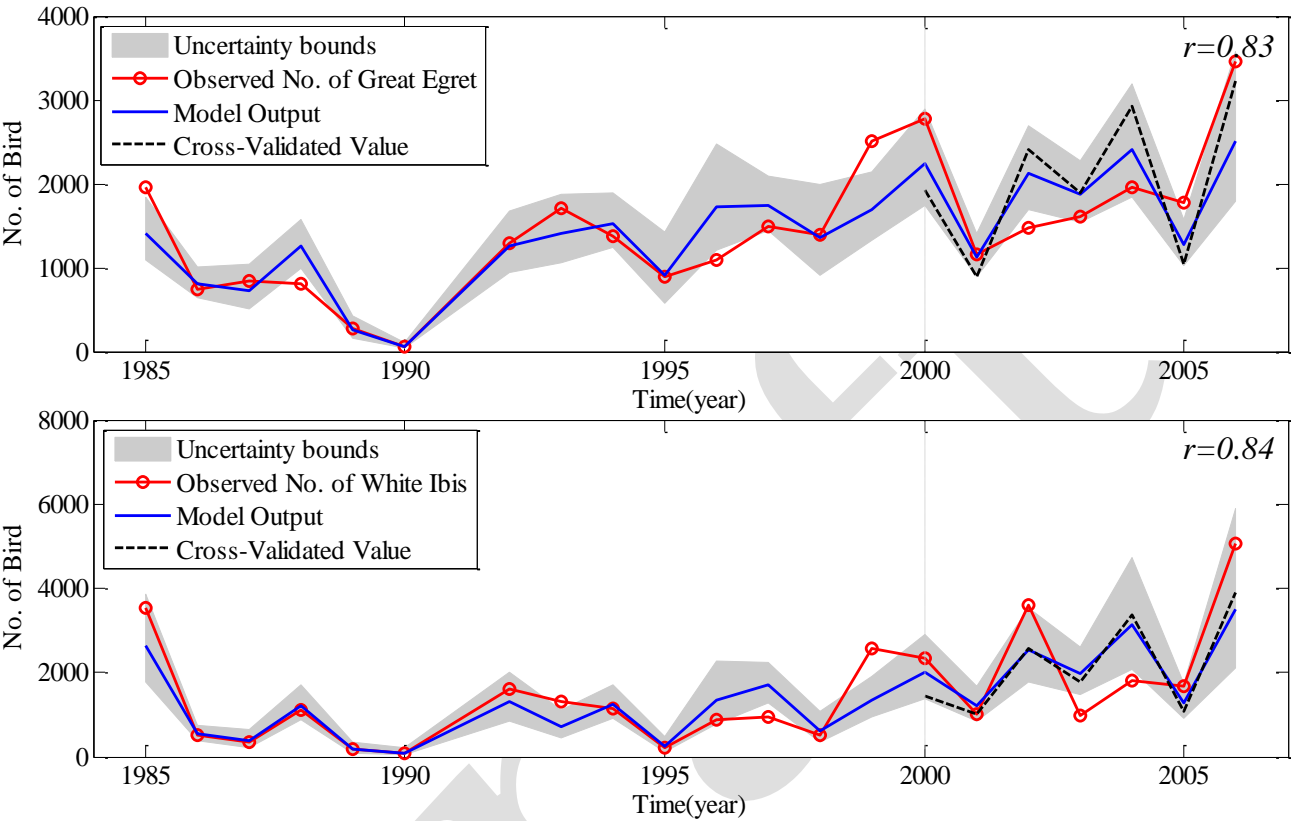
Figure 8

857   **Figure 9**

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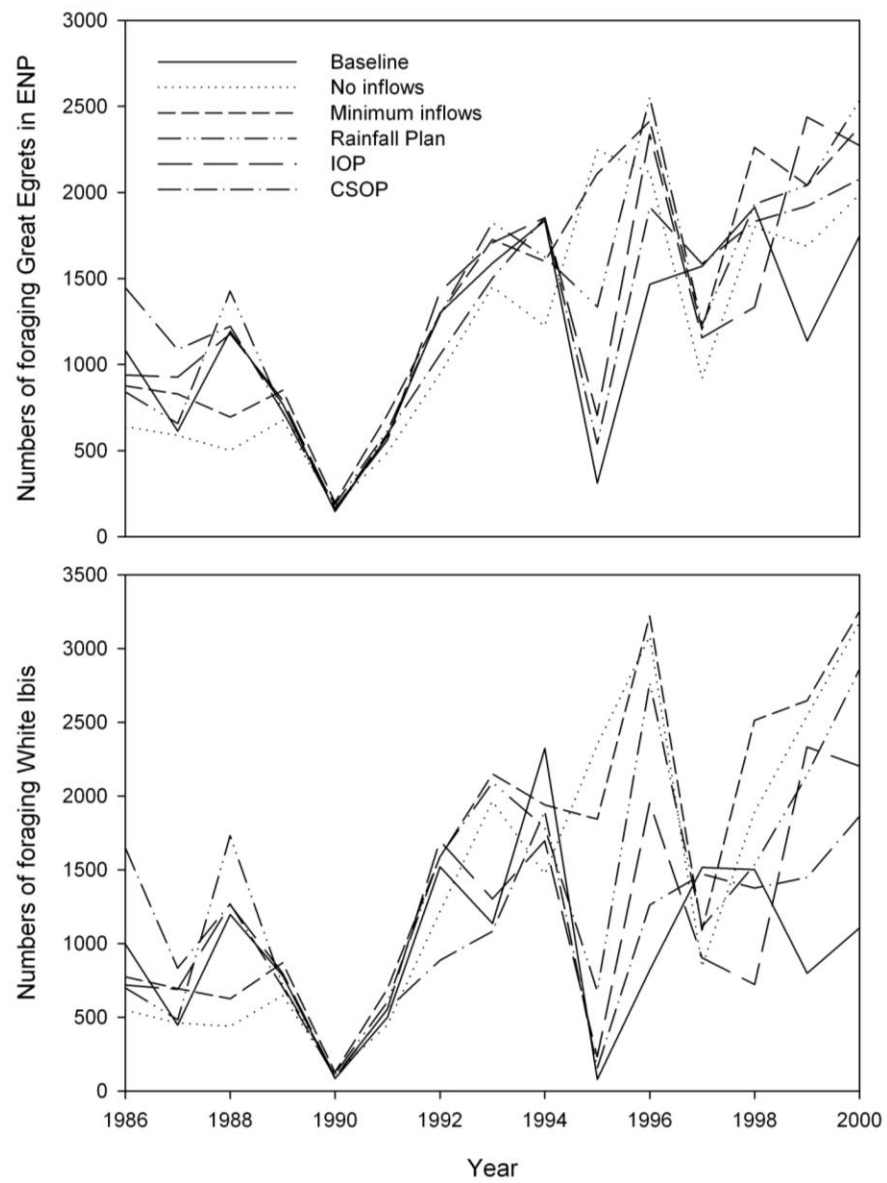

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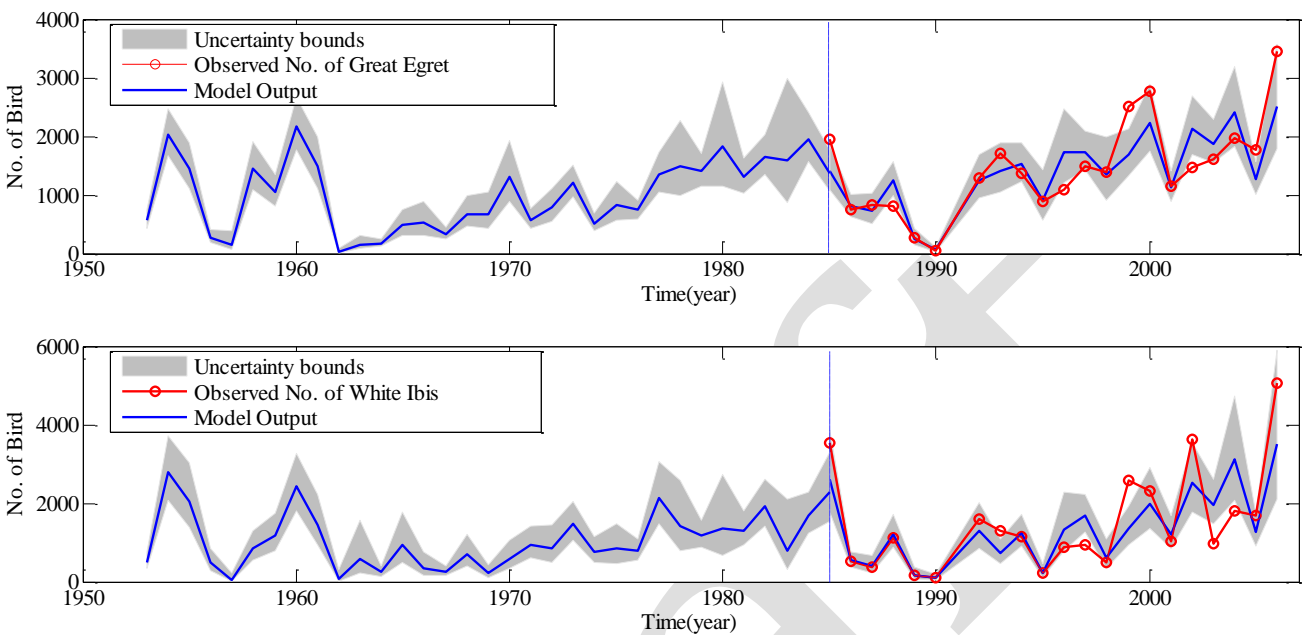
Figure 10

867   **Figure 11**

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871 # Appendix

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873 Model hyperparameters and associated uncertainty bounds for each level of the model

Node		Description	Mean	Stand. Dev.	2.50%	Median	97.50%
Hyperparameter *Mu Beta* **(***i,1***)** **for** *Great Egret*	$\mu_{\beta_{i1}}$	*Initial W.S*	-0.233	0.428	-1.203	-0.171	0.403
		Initial W.S ^{2}	-0.290	0.253	-0.879	-0.260	0.041
		Averaged W.S	0.487	0.548	-0.266	0.516	1.218
		Averaged W.S ^{2}	-0.054	0.580	-0.508	-0.155	2.328
		No. of Disruption	-0.362	0.157	-0.717	-0.346	-0.096
		No. of Disruption ^{2}	-0.078	0.135	-0.312	-0.092	0.258
Hyperparameter *Mu Beta* **(***i,2***)** **for** *White Ibis*	$\mu_{\beta_{i2}}$	*Initial W.S*	-0.290	0.408	-1.224	-0.265	0.391
		Initial W.S ^{2}	-0.297	0.296	-0.908	-0.262	0.054
		Averaged W.S	0.504	0.544	-0.265	0.541	1.220
		Averaged W.S ^{2}	-0.069	0.590	-0.492	-0.179	2.335
		No. of Disruption	-0.391	0.165	-0.719	-0.388	-0.088
		No. of Disruption ^{2}	-0.079	0.137	-0.333	-0.093	0.244
Hyperparameter *Mu (Mu Beta(i))*	$\mu_{\mu_{\beta_i}}$	*Initial W.S*	-0.262	0.527	-1.237	-0.215	0.417
		Initial W.S ^{2}	-0.291	0.303	-0.916	-0.259	0.090
		Averaged W.S	0.497	0.555	-0.280	0.528	1.249
		Averaged W.S ^{2}	-0.068	0.632	-0.512	-0.168	2.341
		No. of Disruption	-0.379	0.189	-0.762	-0.369	-0.072
		No. of Disruption ^{2}	-0.076	0.147	-0.350	-0.092	0.266
Hyperparameter **Sigma(Mu Beta(i))**	$\sigma_{\mu_{\beta_i}}$	*Initial W.S*	0.001	0.001	0.001	0.002	0.004
		Initial W.S ^{2}	0.001	0.001	0.000	0.002	0.003
		Averaged W.S	0.001	0.001	0.001	0.002	0.003
		Averaged W.S ^{2}	0.001	0.001	0.000	0.002	0.003
		No. of Disruption	0.001	0.001	0.000	0.002	0.003
		No. of Disruption ^{2}	0.001	0.001	0.000	0.002	0.003

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